DOCKET NO: 242662US6YA

IN THE UNITED STATES PATENT & TRADEMARK OFFICE

IN RE APPLICATION OF :

KEVIN ANDREW CHAMNESS : EXAMINER: WEST, JEFFREY R.

SERIAL NO: 10/660,697 :

FILED: SEPTEMBER 12, 2003 : GROUP ART UNIT: 2857

FOR: METHOD AND SYSTEM OF DIAGNOSING A PROCESSING SYSTEM USING ADAPTIVE MULTIVARIATE ANALYSIS :

DECLARATION UNDER 37 C.F.R. § 1.131

COMMISSIONER FOR PATENTS
ALEXANDRIA, VIRGINIA 22313

SIR:

I, Ronald A. Rudder, declare and state that:

1. I was the prosecuting attorney who filed the above-identified application.

2. On September 9, 2003, my firm received a copy of the patent application containing the subject matter of the present claims. Shown in Exhibit A along with the accompanying email are excerpts from numbered paragraphs [0054] – [0104] of this copy describing the basic subject matter defined in the claims, especially the subject matter associated with providing updated centering coefficients. The excerpts are nearly identical (except for format) to those corresponding sections of the filed application.

3. On September 10, 2003, my firm received in our office a final revised patent application from the Applicant, including authorization to review and proceed with filing. The email authorization is included in Exhibit B.

4. On September 11, 2003, work proceeded here in our office to prepare the requisite filing papers. Attached in Exhibit C are metadata analysis files showing creation of the filing receipt, priority document, and fee calculation documents on September 11, 2003 for the present application. Also shown in Exhibit C is the Application Data Sheet work log also showing a creation date of September 11, 2003 for the docket number of the present application.

5. On September 12, 2003, as shown in my billed time description attached in Exhibit D, I reviewed the completed filing papers prior to filing.

6. On September 12, 2003, my firm filed the present application as the U.S. Patent and Trademark Office records verify.

7. I further declare that all statements made herein of own knowledge are true and that all statements made on information and belief are believed to be true; and further that these statements my firm re made with the knowledge that willful false statements and the like so made are punishable by fine or imprisonment, or both, under Section 1001 of Title 18 of the United States Code and that such willful false statements may jeopardize the validity of the application or any patent issuing thereon.

Date: 2-20-2007

RONALD A. RUDDER

I:\ATTY\RAR\AMENDMENTS\242662US\242662US DECLARATION1131 2-20-07.DOC

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OIPE IAP15 FEB 20 2007 PATENT & TRADEMARK OFFICE

Ronald Rudder

EXHIBIT A
Appl. NO.: 10/660,697

From:	TEA Strang, Eric [estrang@phx.telusa.com]
Sent:	Tuesday, September 09, 2003 2:28 PM
To:	Ron Rudder; Ellen Currier
Cc:	pcalabrese@phx.telusa.com; Edwin Garlepp
Subject:	RE: ES-004
Categories:	Folder: GroupWise Archive\~INBOX

Ron,

Attached is an amended draft of the above identified case. I have adopted all of Ed's recommended changes and added a few others (highlighted in blue). Please review and prepare for filing. The current draft addresses all of the inventor's comments.

Regards

Eric

<<ES-004-Application-09082003.doc.pgp>>

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window (not shown) to plasma processing region 45. A frequency for the application of RF power to the inductive coil 80 preferably ranges from 10 MHz to 100 MHz and is preferably 13.56 MHz. Similarly, a frequency for the application of power to the chuck electrode preferably ranges from 0.1 MHz to 30 MHz and is preferably 13.56 MHz. In addition, a slotted Faraday shield (not shown) can be employed to reduce capacitive coupling between the inductive coil 80 and plasma. Moreover, controller 55 can be coupled to RF generator 82 and impedance match network 84 in order to control the application of power to inductive coil 80. In an alternate embodiment, inductive coil 80 can be a "spiral" coil or "pancake" coil in communication with the plasma processing region 45 from above as in a transformer coupled plasma (TCP) reactor.

[0051] Alternately, the plasma can be formed using electron cyclotron resonance (ECR). In yet another embodiment, the plasma is formed from the launching of a Helicon wave. In yet another embodiment, the plasma is formed from a propagating surface wave.

[0052] As discussed above, the process performance monitoring system 100 includes plurality of sensors 50 and controller 55, where the sensors 50 are coupled to process tool 10 and the controller 55 is coupled to the sensors 50 to receive tool data. The controller 55 is further capable of executing at least one algorithm to optimize the tool data received from the sensors 50, determine a relationship (model) between the tool data, and use the relationship (model) for fault detection.

[0053] When encountering large sets of data involving a substantive number of variables, multivariate analysis (MVA) is often applied. For example, one such MVA technique includes Principal Components Analysis (PCA). In PCA, a model can be assembled to extract from a large set of data, a signal exhibiting the greatest variance in the multi-dimensional parameter space.

[0054] For example, each set of data parameters for a given substrate run, or instant in time, can be stored as a row in a matrix $\overline{X}$ and, hence, once the matrix $\overline{X}$ is assembled, each row represents a different substrate run, or instant in time (or observation), and each column represents a different data parameter (or data variable) corresponding to the plurality of sensors 50.

Therefore, matrix $\overline{X}$ is a rectangular matrix of dimensions q by r, where q represents the row dimension and r represents the column dimension. Once the data is stored in the matrix, the data is generally mean-centered and/or normalized. The process of mean-centering the data stored in a matrix column involves computing a mean value of the column elements and subtracting the mean value from each element. Moreover, the data residing in a column of the matrix can be normalized by determining the standard deviation of the data in the column.

[0055] Using the PCA technique, the correlation structure within matrix $\overline{X}$ is determined by approximating matrix $\overline{X}$ with a matrix product ($\overline{TP^T}$) of lower dimensions plus an error matrix $\overline{E}$, viz.

[0056] $$\overline{X} = \overline{T}\overline{P^T} + \overline{E},$$

(1a)

[0057] where

[0058] $$\overline{X}_{i,j} = \left(\frac{\overline{X}^*_{i,j} - \overline{X}_{M,j}}{\sigma_{X,j}} \right),$$

(1b)

[0059] "i" represents the i^{th} row, "j" represents the j^{th} column, subscript "M" represents mean value, σ represents standard deviation, $\overline{X}^*$ is a the raw data, $\overline{T}$ is a (q by p) matrix of scores that summarizes the $\overline{X}$–variables, and $\overline{P}$ is a (r by p, where p≤r) matrix of loadings showing the influence of the variables.

[0060] In general, the loadings matrix $\overline{P}$ can be shown to comprise the eigenvectors of the covariance matrix of $\overline{X}$, where the covariance matrix $\overline{S}$ can be shown to be

[0061] $$\overline{S} = \overline{X}^T \overline{X}. \qquad (2)$$

[0062] The covariance matrix $\overline{S}$ is a real, symmetric matrix and, therefore, it can be described as

[0063] $$\overline{S} = \overline{U\Lambda U}^T, \qquad (3)$$

[0064] where the real, symmetric eigenvector matrix $\overline{U}$ comprises the normalized eigenvectors as columns and $\overline{\Lambda}$ is a diagonal matrix comprising

the eigenvalues corresponding to each eigenvector along the diagonal. Using equations (1a) and (3) (for a full matrix of p=r; i.e. no error matrix), one can show that

[0065] $$\overline{P} = \overline{U} \tag{4}$$

[0066] and

[0067] $$\overline{T}^T \overline{T} = \overline{\Lambda}. \tag{5}$$

[0068] A consequence of the above eigen-analysis is that each eigenvalue represents the variance of the data in the direction of the corresponding eigenvector within n-dimensional space. Hence, the largest eigenvalue corresponds to the greatest variance in the data within the multi-dimensional space whereas the smallest eigenvalue represents the smallest variance in the data. By definition, all eigenvectors are orthogonal, and therefore, the second largest eigenvalue corresponds to the second greatest variance in the data in the direction of the corresponding eigenvector, which is, of course, normal to the direction of the first eigenvector. In general, for such analysis, the first several (three to four, or more) largest eigenvalues are chosen to approximate the data and, as a result of the approximation, an error $\overline{E}$ is introduced to the representation in equation (1a). In summary, once the set of eigenvalues and their corresponding eigenvectors are determined, a set of the largest eigenvalues can be chosen and the error matrix $\overline{E}$ of equation (1a) can be determined.

[0069] An example of commercially available software which supports PCA modeling is MATLAB™ (commercially available from The Mathworks, Inc., Natick, MA), and PLS Toolbox (commercially available from Eigenvector Research, Inc., Manson, WA).

[0070] Additionally, once a PCA model is established, commercially available software, such as MATLAB™, is further capable of producing as output other statistical quantities such as the Hotelling T^2 parameter for an observation, or the Q-statistic. The Q-statistic for an observation can be calculated as follows

[0071] $$Q = \overline{E}^T \overline{E}, \tag{6a}$$

[0072] where

[0073] $$\overline{E} = \overline{X}\left(\overline{I} - \overline{P}\overline{P}^T\right),$$

(6b)

[0074] and $\overline{I}$ is the identity matrix of appropriate size. For example, a PCA model (loadings matrix $\overline{P}$, etc.) can be constructed using a "training" set of data (i.e. assemble $\overline{X}$ for a number of observations and determine a PCA model using MATLAB™). Once the PCA model is constructed, projections of a new observation onto the PCA model can be utilized to determine a residual matrix $\overline{E}$, as in equation (1).

[0075] Similarly, the Hotelling T^2 can be calculated as follows

[0076] $$T^2{}_i = \sum_{a=1}^{p} \frac{\overline{T}^2{}_{ia}}{s^2{}_{ta}},$$

(7a)

[0077] where

[0078] $$\overline{T} = \overline{XP},$$

(7b)

[0079] and T_{ia} is the score (from equation (7b)) for the i^{th} observation (substrate run, instant in time, etc.; i.e., i=1 to q) and the a^{th} model dimension (i.e., a=1 to p), and s^2_{ta} is the variance of $\overline{T}_a$. For example, a PCA model (loadings matrix $\overline{P}$, etc.) can be constructed using a "training" set of data (i.e. assemble $\overline{X}$ for a number of observations and determine a PCA model using MATLAB™). Once the PCA model is constructed, projections of a new observation onto the PCA model can be utilized to determine a new scores matrix $\overline{T}$.

[0080] Typically, a statistical quantity, such as the Q-statistic, or the Hotelling T^2, is monitored for a process, and, when this quantity exceeds a pre-determined control limit, a fault for the process is detected.

[0081] FIG. 6A shows an example of conventional use of a PCA model to monitor the Q-statistic (Q-factor) of a process in order to determine faults in the process. In the example of FIG. 6A, the model is applied to process data acquired from Unity II DRM (Dipole Ring Magnet) CCP (Capacitively Coupled Plasma) processing systems (commercially available from Tokyo Electron Limited; see FIG. 3) that perform a patterned oxide etch with a $C_4F_8/CO/Ar$ +

O_2 based chemistry. This processing system operates in a batch mode with a fixed process recipe for each lot. Typically, a single recipe is utilized from lot to lot for a particular process step in the manufacture of a device. The same processing system is frequently utilized for many different device layers and steps, but for each process step, the recipe remains the same.

[0082] The data parameters collected include the chamber pressure, applied power, various temperatures, and many other variables relating to the pressure, power, and temperature control as shown in Table 1.

[0083] The process recipe used in this example has three main steps: a photoresist cleaning step, a main etch step, and a photoresist stripping step. The scope of this example applied to the main etch step, but it is not limited to this particular step or any particular step and is, therefore, applicable to other steps as well.

[0084] For each process step, an observation mean and observation standard deviation of a time trace for each data parameter (or tool variable) was calculated from roughly 160 samples for each substrate. The beginning portion of the time trace for each data parameter, where the RF power increases, was trimmed in these statistical calculations in an attempt to remove the variation due to the power when it is turned on.

[0085] In the example of FIG. 6A, a PCA model was performed for the first 500 substrates using the same recipe in a single processing system. The standard PCA methods implemented in MATLAB™ were used, with mean centering and unit variance scaling. Also, the standard Q residuals (SPE) and Q contributions were calculated using the Eigenvector Research PLS Toolbox offered by Eigenvector Research as an add-on to MATLAB™.

[0086] In the example of FIG. 6A, the PCA model was constructed from the first 500 substrates in a first processing system and was applied to all 3200 substrates from this processing system. As seen in this figure, the resulting Q statistic exceeds the 95% confidence limit in the model within less than 250 substrates after the PCA model was built (i.e. by substrate number 750), and never returns to below that level. In addition, distinct outliers and distinct step-like changes are apparent. Thus, FIG. 6A demonstrates that while a conventional PCA model constructed as described above can be used to monitor the Q-statistic, there exist periods of time where the statistical

parameter deviates above the control limit never to return below. Indeed, any of the above described statistics (e.g., the Q-statistic, or the Hotelling T^2 parameter) can be monitored using a given model for a specific process in a specific processing system, but will eventually deviate above the control limit never to return below. Thereafter, the model is no longer applicable to the given process and given processing system.

[0087] While methods are known for preserving the usefulness of the PCA model over long process runs, the present inventors have recognized that these methods are not practical for commercial application to semiconductor manufacturing process control. For example, using an adaptive model technique, the PCA model can be actually rebuilt with each process run in order to update the model on the fly during the process. While this adaptive modeling technique may generally stabilize the statistical monitoring within a given control limit, it requires computational resources not practical for commercial processes.

[0088] Another technique for maintaining the usefulness of the statistical monitoring of FIG. 6A is to employ a more complicated control limit scheme. Specifically, the control limit can be reset for each process run based on a predicted degradation of the PCA model. While this method will avoid the indication of an out-of-process condition due to degradation of the PCA model, changing the control limit with each process run requires a complex scheme that is also impractical for commercial processes.

[0089] Thus, the present inventors have recognized that conventional methods for adapting a PCA model to enable statistical monitoring over long process runs is impractical for commercial processes. More specifically, the present inventors have discovered that the standard approach to centering and scaling the data in a PCA matrix has not enabled the development of a robust model capable of use for long periods of time (i.e., substantive number of substrate runs).

[0090] In an embodiment of the present invention, an adaptive multivariate analysis is described for preparing a robust PCA model. Therein, the centering and scaling coefficients are updated using an adaptation scheme. The mean values (utilized for centering) for each summary statistic are

updated from one observation to the next using a filter, such as an exponentially weighted moving average (EWMA) filter shown as follows:

[0091] $$\overline{X}_{M,j,n} = \lambda \overline{X}_{M,j,n-1} + (1-\lambda)\overline{X}_{j,n}, \quad (8)$$

[0092] where $\overline{X}_{M,j,n}$ represents the calculated model mean value ("M") of the j[th] data parameter at the current run (or observation "n"), $\overline{X}_{M,j,n-1}$ represents the calculated model mean value ("M") of the j[th] data parameter at the previous run (or observation "n-1"), $\overline{X}_{j,n}$ represents the current value of the j[th] data parameter for the current run, and λ is a weighting factor ranging from a value of 0 to 1. For example, when λ=1, the model mean value utilized for centering each data parameter is the previously used value, and, when λ=0, the model mean value utilized for centering each data parameter is the current measured value.

[0093] The model standard deviations (utilized for scaling) for each summary statistic are updated using the following recursive standard deviation filter

[0094] $$\sigma_{X,j,n} = \sqrt{(\sigma_{X,j,n-1})^2\left(\frac{k-2}{k-1}\right) + \tfrac{1}{k}\left(\overline{X}_{j,n} - \overline{X}_{M,j,n}\right)^2}, \quad (9)$$

[0095] where $\sigma_{X,j,n}$ represents the calculated model standard deviation of the j[th] data parameter for the current run (or observation "n"), $\sigma_{X,j,n-1}$ represents the calculated model standard deviation of the j[th] data parameter for the previous run (or observation "n-1"), n represents the run (or observation) number, and k represents a filter constant. The filter constant k can, for example, be selected as a constant less than or equal to N, where N represents the number of substrate runs, or observations, utilized to construct the PCA model.

TABLE 1.

Area	Variable	Description
Gas Flow and Pressure	PRESSURE	Chamber Pressure
	APC	Throttle Valve Angle
	Ar	Ar Flow Rate
	C4F8	C4F8 Flow Rate
	CO	CO Flow Rate
Power and Matching	RF-FORWARD-LO	Lower Electrode Power
	C1-POSITION-LO	Matching Network Capacitor 1
	C2-POSITION-LO	Matching Network Capacitor 2
	MAGNITUDE	Matcher Magnitude
	PHASE	Matcher Phase
	RF-VDC-LO	Lower Electrode DC Voltage
	RF-VPP-LO	Lower Electrode Peak to Peak Voltage
ES Chuck	ESC-CURRENT	Electrostatic Chuck Current
	ESC-VOLTAGE	Electrostatic Chuck Voltage
Temperature and Cooling	LOWER-TEMP	Lower Electrode Temperature
	UPPER-TEMP	Upper Electrode Temperature
	WALL-TEMP	Wall Temperature
	COOL-GAS-FLOW1	He Edge Cooling Flow Rate
	COOL-GAS-FLOW2	He Center Flow Rate
	COOL-GAS-P1	He Edge Cooling Gas Pressure
	COOL-GAS-P2	He Center Cooling Gas Pressure

[0096] FIG. 6B shows the same example of using a PCA model to monitor the Q-statistic that was presented in FIG. 6A, except that the centering and scaling coefficients are updated using an adaptation scheme in accordance with the present invention. As seen in this figure, after the first 500 wafers, when the centering and scaling constants are adapted using adaptive centering and scaling coefficients described above (λ=0.92; k=500), the Q-statistic chart is substantially more stable across all of the remaining substrates, and the data predominantly resides within the same limit. The inventive adaptation scheme provides similar improvement to other statistical monitoring schemes (e.g., the Hotelling T^2 parameter). Thus, adaptation of the PCA model in accordance with the present invention allows for a more robust PCA model that can be used for long process runs.

[0097] Referring now to FIGs. 6A and 6B together, the first excursion of substantive magnitude is the run with the largest Q value in the adaptive case,

which occurs for substrate 1492. In the residual contribution plots for both the static and adaptive cases (see FIG. 7), C1-POSITION-LO mean, RF-VPP-LO mean, and ESC-CURRENT are the extreme values. The arbitrarily scaled summary statistics for the latter two data parameters are plotted in FIG. 8. These three data parameters account for the large spikes in the data at four points, which could indicate an issue with the impedance match network system. This type of outlier is clear in both Q charts, but only the adaptive case allows for a fixed limit (e.g., 95% confidence limit) for all time.

[0098] In another embodiment, the relative change in the centering and scaling coefficients can be calculated to alert the operator or engineer that step summary statistics have shifted between two runs, or observations. For each centering coefficient, this is done by subtracting the estimate at an initial run from the estimate at a final run, then scaling each difference by the standard deviation used for scaling that step statistic for the initial run, viz.

[0099]
$$M_{\overline{X}} = \left| \frac{\overline{X}_{M,j,b} - \overline{X}_{M,j,a}}{\sigma_{j,a}} \right|, \qquad (10)$$

[00100] where $M_{\overline{X}}$ is the model mean movement metric, $\overline{X}_{M,j,a}$ represents the model mean value for the jth data parameter for the ath substrate, $\overline{X}_{M,j,b}$ represents the model mean value for the jth data parameter for the bth substrate, and $\sigma_{j,a}$ represents the model standard deviation for the jth data parameter for the ath substrate.

[00101] For the scaling coefficient, the calculation is the difference in standard deviations scaled with the mean used for centering that step statistic, viz.

[00102]
$$M_{\sigma} = \left| \frac{\sigma_{j,b} - \sigma_{j,a}}{\overline{X}_{M,j,a}} \right|, \qquad (11)$$

[00103] where $\sigma_{j,b}$ represents the model standard deviation for the jth data parameter for the bth substrate.

[00104] These results are then displayed in a Pareto chart to identify the variables that exhibited the largest relative change during the period. For example, this supplement to the typical contribution plot can give the operator

insight on the global changes in the set of data parameters. In contrast, the contribution plot indicates the local deviation in a particular run.

[00105] Referring again to FIGs. 6A and 6B, the next type of excursion is observed at steps in the input summary data. In the static case, these excursions are clearly evident in the Q chart, although automating detection of these changes proves to be quite difficult. In the adaptive case, there are only 4 periods where the Q statistic violates the confidence limit for more than 5 consecutive substrates (starting at substrates 1880, 2535, 2683, and 2948). When the model mean movement metric is calculated about each of these four periods (from the substrate before the period to the substrate after the period), the most extreme values occur for 1880 and 2946 on C1-POSITION-LO mean and WALL-TEMP mean, respectively. FIG. 9A presents the model mean movement metric and the model standard deviation metric for all of the data parameters. The arbitrarily scaled summary data for the two data parameters is displayed in FIG. 9B. The two major changes in the Q statistic seem to be dominated by these two data parameters. For example, the shift in these data parameters may have been caused by a tool cleaning, e.g., replacing key parts and changing the electrical or heat transfer characteristics of the processing system. Although the temperature is regulated in the processing system, this is done only at the upper electrode and walls. The lower temperature is not controlled and could be affected by different materials or part configurations in the processing system. The contribution plots for the static case and the adaptive case for substrate 1880 both are dominated by the C1-POSITION-LO. For substrate 2948, WALL-TEMP is the dominant contribution in the adaptive case, but in the static case it is only slightly larger than the C1-POSITION-LO value (which does not change at this run).

[00106] In addition to providing a more robust PCA model that can be used for statistical monitoring over long process runs, the adaptive technique also provides use of the same PCA model among different processing systems. FIGs. 10 and 11 illustrate a second example of the present invention wherein, after looking at the major changes over time for one processing system, the same model from the first 500 substrates was then applied to a set of 800 substrates from a second processing system. As seen in FIG. 10, the plot of

Ronald Rudder

From:	TEA Strang, Eric [estrang@phx.telusa.com]
Sent:	Wednesday, September 10, 2003 6:51 PM
To:	Ron Rudder; Ellen Currier
Cc:	pcalabrese@phx.telusa.com
Subject:	RE: ES-004
Categories:	Folder: GroupWise Archive\~INBOX

EXHIBIT B
APPl. NO: 10/660,697

Ron,

Attached is an amended draft for the above identified case. I have accepted your recommended changes, and made a few additional changes (highlighted in blue). Also, regarding the abstract, I will defer to your recommended approach (please proceed). Otherwise, please review and prepare for filing.

Regards

Eric

<<ES-004-Application-ES-09102003.doc.pgp>>

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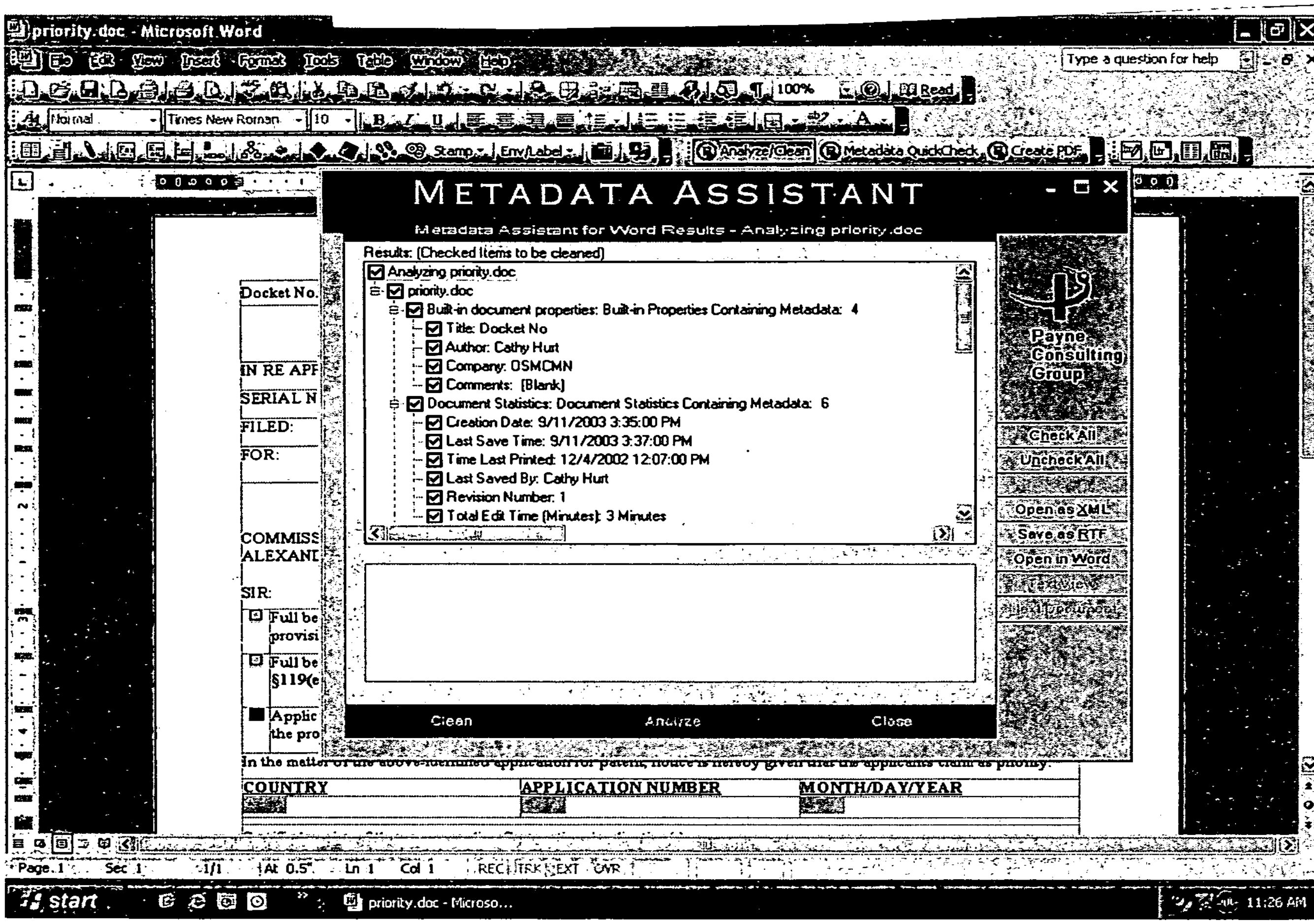
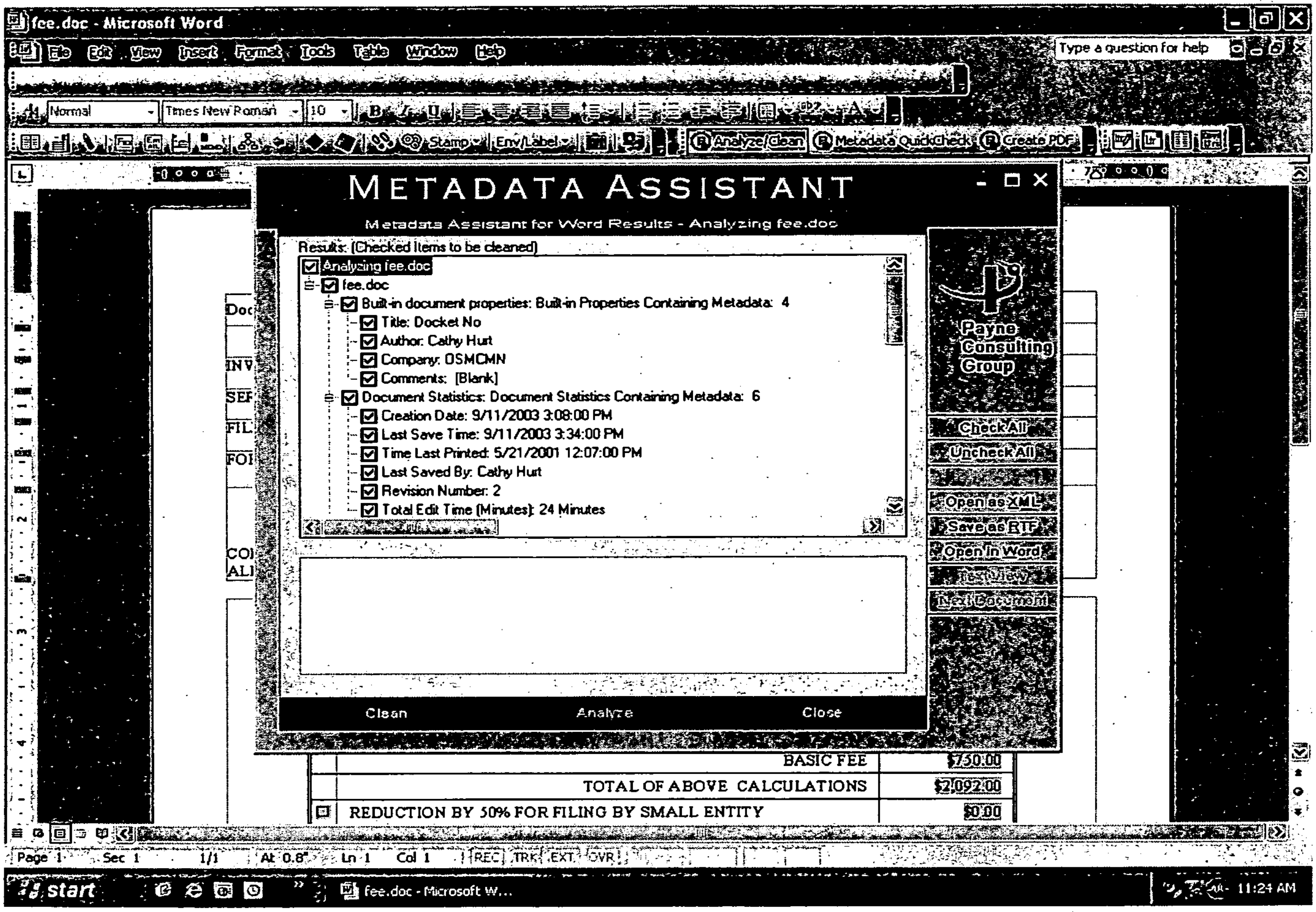
EXHIBIT C
Appl. No.: 10/660,697

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Title: Docket No
Author: Cathy Hurt
Company: OSMCMN
Comments: [Blank]
Document Statistics: Document Statistics Containing Metadata: 6
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Last Save Time: 9/11/2003 3:34:00 PM
Time Last Printed: 5/21/2001 12:07:00 PM
Last Saved By: Cathy Hurt
Revision Number: 2
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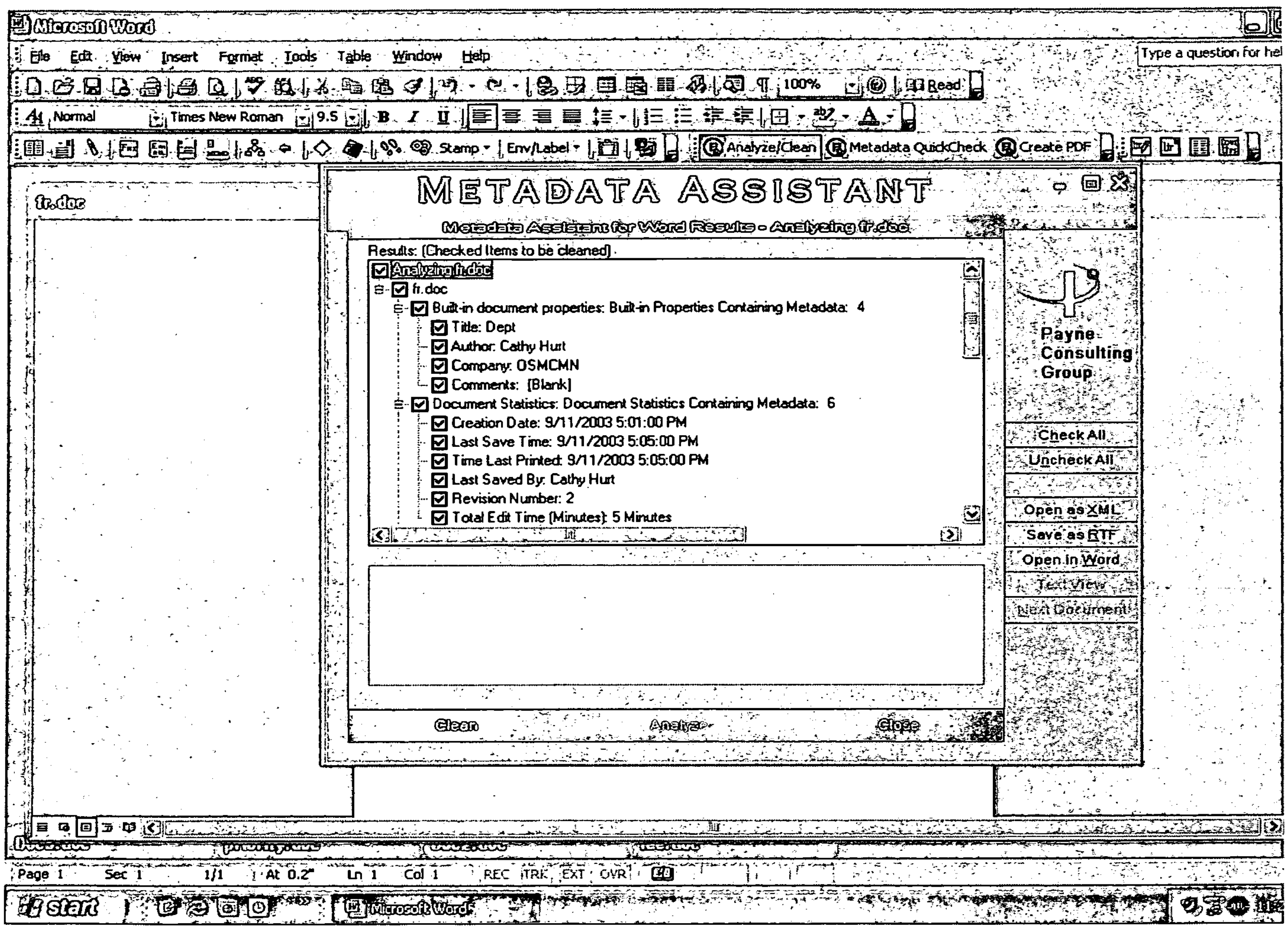
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Author: Cathy Hurt
Company: OSMCMN
Comments: [Blank]
Document Statistics: Document Statistics Containing Metadata: 6
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Last Save Time: 9/11/2003 5:05:00 PM
Time Last Printed: 9/11/2003 5:05:00 PM
Last Saved By: Cathy Hurt
Revision Number: 2
Total Edit Time (Minutes): 5 Minutes
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DOCKET NUMBER	AUTH	DATE	TITLE
242635US6RD	MLH	9/24/2003	SPIN-TUNNEL TRANSISTOR AND MAGNETIC REPRODUC
242636US90	DLB	9/11/2003	TRANSMITTER FOR SURVEILLANCE CAMERA SYSTEM
242637US0PCT	tem	9/16/2003	METHOD FOR PRODUCING MOULDED BODIES COMPRIS
242638US2PCT	tem	9/15/2003	DIGITAL CIRCUIT TRANSMISSION DEVICE
242641US0CONT	CPU:mb	9/15/2003	POLYVINYL ALCOHOL POLYMER FILM AND POLARIZATI
242646US2 DIV	RFF/ys	9/15/2003	ENCAPSULATED SURFACE ACOUSTIC WAVE COMPONE
242646US2 DIV (SUP)	RFF/ys	11/22/2004	ENCAPSULATED SURFACE ACOUSTIC WAVE COMPONE
242648US0PCT	tem	9/10/2003	CATALYST FOR SYNTHESIZING UNSATURATED ALDEHY
242648US0PCT (SUP)		2/6/2004	CATALYST FOR THE SYNTHESIS OF AN UNSATURATED
242648US0PCT (SUP)	wmj	2/6/2004	CATALYST FOR THE SYNTHESIS OF AN UNSATURATED
242649US2	ALS	9/10/2003	OPTICAL FIBER AXIAL ALIGNMENT METHOD AND RELA
242650US0CONT	DJP/km	9/10/2003	METHODS OF TREATING NEUROLOGICAL CONDITIONS
242654US2CONT	mac	9/17/2003	AUTOFOCUS APPARATUS
242662US	CLHUR	9/11/2003	METHOD AND SYSTEM OF DIAGNOSING A PROCESSING

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Ronald Rudder

From: Thuy B. Luu
Sent: Tuesday, February 13, 2007 6:47 AM
To: Ronald Rudder
Subject: 242662US

EXHIBIT D
APPL. NO: 10/660,697

Ron,

Here is the entry that was performed by you under docket 242662US

9/12/03 - Completed filing package and final review of the application. .5 hrs - $122.50

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